Modelling the transmission mechanism of monetary policy in emerging market countries using prior information

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1. Introduction

In recent years, central banks in emerging market and transition economies (EMCs) have devoted considerable resources to developing macroeconometric models of the transmission mechanism of monetary policy (MTM). Arguably the most important reason for this is that central banks are increasingly gearing monetary policy directly towards achieving their ultimate goal of price stability - in some cases through the adoption of explicit inflation targeting - rather than indirectly through the use of nominal exchange rate objectives. To bolster efforts to implement a broad-based strategy with flexible exchange rates, it is desirable for policymakers to have a firm sense of the size, lag and duration of the effect of interest rate changes on inflation and macroeconomic conditions more broadly. By contrast, under fixed exchange rates, the setting of interest rates is determined by the need to maintain exchange rate stability. Knowledge of the transmission mechanism is always desirable, but in this case it is not strictly needed.

In addition to helping guide the setting of policy, having explicit models of the MTM is also desirable for a number of related reasons. First, an econometric model can be used to provide forecasts of future macroeconomic conditions. This is one reason why modelling the transmission mechanism is of interest also under fixed exchange rates regimes. Second, econometric models can be used to analyse past policy decisions. This may be particularly useful in reviewing episodes in which policy errors were made. Third, econometric simulations may be helpful in communicating policy decisions to the public. Decisions to change interest rates can thus be motivated by pointing to forecasts of macroeconomic conditions. Finally, econometric models can be used to assess and represent the degree of uncertainty about the likely future course of the economy and the impact of policy measures.

Developing models of the MTM in EMCs involves making important decisions regarding the modelling strategy. One central concern is how to deal with the paucity of data for many of these countries. In this note, we review ongoing work at the BIS on these issues.

2. Modelling approach

An important question in studying the MTM concerns the choice of modelling approach. One aspect of this is the size of the model. While some central banks rely upon large models, comprising potentially several hundreds of equations and identities, others prefer more parsimonious models of, say, fewer than 10 equations. Some models are based explicitly on the optimal decisions of economic agents, others contain directly posited equations that have a vaguer link to economic theory, and still others are merely time series econometric models. Furthermore, there are the questions of how to obtain values for parameters and how to specify shock processes. The main point is that there are many decisions to be made in obtaining a model usable for policy analysis, and the choices across central banks are rarely the same.

The modelling of the MTM currently being undertaken at the BIS focuses on small empirical models. The main reasons for the choice of this approach are as follows. First, given that our interest is in comparing the transmission mechanism in several countries, using small empirical models is particularly attractive. As the dimension of a model increases, the possibility of making meaningful comparisons diminishes. Related to this, small models are inherently more transparent than larger models, so that understanding the importance of any given component in the model is enhanced. The ability to isolate the influence of individual parameters in simulation results is illuminating. More generally, the transparency of a model may be critical in persuading senior central bank staff about the usefulness of econometric models for policy purposes. Third, small models are much easier to handle from a technical perspective. For instance, they may be estimated as a whole in a way that exploits all the information in the data. Moreover, confidence intervals for forecasts and simulations can easily be constructed, which makes it possible to communicate the inherent uncertainty of the monetary transmission mechanism and the future path of the economy. Estimating and maintaining a small group of models is simply more tractable.

Given the preference for small, empirical models of the transmission mechanism, two classes of feasible models come to mind. The first is Structural Vector Autoregressions (SVAR). One argument in favour of SVARs is that they are easy to estimate in that the underlying equations can typically be estimated sequentially using single-equation techniques. However, in order to give the results an economic interpretation, the residuals from the fitted equations must be transformed into structural shocks. This requires some identifying assumptions to be made. While a range of such assumptions have been used in the literature, the results are often surprisingly sensitive to the exact choice of assumptions and, more worrisomely, to seemingly innocuous changes in them. A further problem with SVARs is that it is not possible to give a structural interpretation to estimated parameters. As noted above, this may render it more difficult to persuade the central bank's senior management of the benefits of using a model.

The second class is Small Structural Models (SSM). SSMs also have strengths and weaknesses. One strength is that it is possible to give individual equations and parameters economic interpretation. Thus, it is possible to analyse how the results depend on various critical parameters, such as the slope of the Phillips curve or the real interest elasticity of aggregate demand. However, SSMs rely on even stronger identifying assumptions than SVARs, upon which the interpretation of results crucially hinges.

3. Modelling issues

A major problem in modelling the MTM in emerging market and transition economies arises from a lack of good data. Three factors tend to limit the amount of usable data available. First, data on many important macroeconomic variables are not available at all or only for short time periods. For instance, data on wages, which play a critical role in the inflation process, are typically not available for long time periods. Second, even when extended time series are available, the occurrence of structural breaks frequently limits the "effective" sample length. EMCs typically undergo rapid structural change associated with economic development. Moreover, regulatory and institutional changes, including financial deregulation, may introduce large breaks in economic relationships. Thus, data from the pre-change period may be of little value in assessing the behaviour of the economy more recently. Needless to say, this problem is particularly acute for transition economies, for which data from before the early 1990s may be of no value. Third, the quality of the data may be low. It is well known that many if not most macroeconomic time series are subject to measurement errors of unknown importance. For instance, measurement errors on inflation arise because of changes in consumers' spending patterns and because of changes in the quality of goods purchases. These changes are believed to be particularly acute for EMCs.

The potential importance of data problems has consequences for the modelling of the transmission mechanism, and macroeconomic relationships more broadly, in EMCs. With short sample periods and noisy data, the errors of fitted relationships will have a large variance, implying that the parameters will be imprecisely estimated.[1] This may lead researchers to incorrectly disregard important channels of transmission.

One way to deal with this problem in applied work is to impose values for those key parameters that are imprecisely estimated. This approach has the obvious attraction that while a parameter may be poorly identified in a given sample, there may be other information about its value. Such information may come from past research or studies on other countries, or policymakers may have rules of thumb regarding the size of some economic effects. As an illustration, consider a model builder who has to assess the pass-through of exchange rate changes to inflation in an economy which a year ago

[1] In addition, measurement errors on the independent variables will lead to biased estimates.

adopted floating exchange rates after having operated under fixed exchange rates for a decade or two. While the policy change invalidates estimates of the pass-through based on recent data, it may be that parameter estimates for the pass-through parameters from an earlier period of floating rates can be used. Alternatively, estimates for other countries with a similar economic structure may be used to gauge plausible values for the key parameters.

However, imposing values for parameters is not without problems. To see this, note that although a large error variance (eg due to a short sample period) reduces the significance of an estimated parameter, the fitted value is nevertheless an unbiased estimate of the true parameter (in the absence of measurement error). Moreover, imposing values for parameters amounts to disregarding information in the valid part of the sample at hand. A second problem with imposing values is that it understates the degree of uncertainty about the structure of the economy. Central banks have in recent years increasingly recognised that it is important to assess not only the expected impact of policy measures on the future economic conditions but also the degree of uncertainty inherent in such projections. While model builders may be uncertain about the likely size of a parameter, imposing a value for it is tantamount to pretending to be omniscient about the parameter since estimated confidence bands for impulse responses or forecasts will not reflect the true uncertainty about the value of the parameter. Furthermore, the degree of uncertainty regarding the transmission mechanism affects the optimal strength and timing of policy changes. In the light of these problems, it is desirable to explore ways to combine modellers' prior views of the size of individual parameters with the information in the data, while taking into account the uncertainty about the priors.

4. Mixed estimation

One way to do so is to employ *mixed estimation*, which has a long history in econometrics going back to Theil and Goldberger (1961).[2] The starting point for this analysis is the assumption that the modeller has two separate pieces of information about the structure of the economy. The first of these is a data sample, which can be used to estimate the parameters of interest. For example, consider a linear model, and collect all of the parameters of the model in the vector β. Let $\beta(ols)$ denote a vector of estimated parameters obtained by a conventional classical estimation method (eg OLS), and $\Sigma(ols)$ its covariance matrix. The second piece of information consists of the prior information of the modeller (or policymaker). Let $\beta(prior)$ denote the prior information regarding the vector of parameters of interest, and let $\Sigma(prior)$ denote the associated covariance matrix. The practice of imposing an exact value for a parameter corresponds to assuming that $\Sigma(prior) = 0$.

Given the above information, the estimate of the parameter vector, and associated covariance matrix, that optimally combine the two pieces of information are given by:

$$\beta(post) = F\beta(prior) + (I - F)\beta(ols) \tag{1}$$

where

$$F = \left[\Sigma(prior)^{-1} + \Sigma(ols)^{-1}\right]^{-1}\Sigma(prior)^{-1} \tag{2}$$

$$\Sigma(post) = \left[\Sigma(prior)^{-1} + \Sigma(ols)^{-1}\right]^{-1} \tag{3}$$

Thus, equation (1) implies that $\beta(post)$, the "mixed estimate" of the parameters of interest, is a weighted average of $\beta(ols)$, the OLS estimate, and $\beta(prior)$, the prior estimate. The weight on the prior information depends on the confidence the modeller attaches to it. To see this more clearly,

[2] H Theil and A S Goldberger (1961), "On pure and mixed estimation in economics", *International Economic Review*, 2 65-78. Our treatment of mixed estimation also has an interpretation as Bayesian estimation under natural conjugate priors with known covariance matrix of the residual.

consider the case of a single parameter, in which case we have that $\Sigma_i = \sigma_i^2$ for *i = ols,prior,post*. Using this notation, we have that:

$$F = \frac{\sigma_{ols}^2}{\sigma_{ols}^2 + \sigma_{ols}^2} \tag{4}$$

which implies that the weight attached to the prior information is increasing in the uncertainty over the estimate from the sample $\left(\sigma_{ols}^2\right)$ and decreasing in the modeller's confidence regarding the prior information of the parameter $\left(\sigma_{prior}^2\right)$. Note that, if the modeller is certain about the true value of the parameter, and *F* = 1. Thus, the mixed estimate of the parameter will equal the prior value. By contrast, if the modeller is very uncertain about the true value of the parameter, $\sigma_{prior}^2 = \infty$ and *F* = 0, so that the mixed estimate will be based solely on the data sample.

So far the discussion has focused on the implication of prior information for the point estimates of the parameters. However, prior information also influences the uncertainty of the mixed estimates. To see this, rewrite (3) for the scalar case:

$$\sigma_{post}^2 = \frac{1}{\left[\dfrac{1}{\sigma_{prior}^2} + \dfrac{1}{\sigma_{ols}^2}\right]} \tag{5}$$

which has several interesting implications. Note that $0 \leq \sigma_{post}^2 \leq \sigma_{ols}^2$ and $\sigma_{prior}^2 = \infty$ implies that $\sigma_{post}^2 = \sigma_{ols}^2$. Thus, the precision of the mixed estimate is at least as high as the precision of the estimate based solely on the data, with the former converging to the latter as the degree of prior uncertainty increases.

5. Empirical illustration

In this section, we illustrate how the approach discussed above can be used to provide estimates of the transmission mechanism. The analysis is conducted using a simple model of the economy consisting of two equations. The first of these is an aggregate demand relationship, according to which the output gap, y_t, depends on its own lagged value and the short-term real interest rate (lagged two periods), r_{t-2}, which we take as the policy instrument:[3]

$$y_t = a_1 y_{t-1} + a_2 r_{t-2} + \varepsilon_t^y \tag{6}$$

The second relationship is a backward-looking Phillips curve, according to which inflation, π_t, depends on the lagged output gap, lagged inflation and other (observable) exogenous variables, y_t:

$$\pi_t = b_1 y_{t-1} + b_2 \pi_{t-1} + b_3 z_t + \varepsilon_t^\pi \tag{7}$$

The MTM is straightforward in this model: an increase in real short-term interest rates reduces future output gaps, which in turn reduces future inflation. The key parameters for assessing the impact of policy are thus a_2 and b_1. Of course, a_1 and b_2 are also important in that they determine the dynamic response of the economy to disturbances.

Next, we estimate a version of this model for South Africa, using annual data for the period 1985-2000. To capture open-economy aspects in the model, we specify z_t to be relative import prices (lagged

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3 Constants are omitted.

twice). Table 1 provides OLS estimates of the parameters. As can be seen, the impact of short-term real interest rates on the output gap, a_2, is highly significant. Thus, the first step of the transmission mechanism is well identified. By contrast, the impact of the output gap on inflation, b_1, is highly insignificant. The initial impact of monetary policy on inflation, which occurs with a lag of three years, is given by a_2b_1. The imprecision of this estimate is illustrated in Graphs 1 and 2, which show impulse responses to a 100 basis point increase in the real interest rate maintained for one year.

To illustrate how mixed estimation can be used to study the transmission mechanism, we next assume that we have prior information regarding these parameters.[4] In particular, for one parameter (in this case, a_2), we assume that the prior mean and its variance are similar to the values obtained by OLS estimation. Specifically, our prior for a_2 has a normal distribution with mean -0.3 and a standard error of 0.1.[5] It is worthwhile pointing out that, even when the prior information is similar to that in the data, there may be important benefits in using mixed estimation. To see this, consider Graph 3, which shows the sampling distribution of the OLS estimator, the assumed prior probability distribution, and the resulting distribution of the mixed estimator. Although the assumed prior and the OLS estimates are similar, the distribution of the posterior is considerably more peaked, indicating that combining the information from the data with the prior leads us to a more certain view about the true value of the parameter.

Next we consider prior information regarding b_1, which captures the impact of the output gap on inflation. We assume that this parameter has a mean of 0.2 and standard deviation of 0.1. Thus, the prior mean is somewhat below the OLS estimate of 0.3. The main difference between the prior and sampling distributions, however, lies in their precision: whereas a 95% confidence band based on OLS estimation spans the range -0.22 to 0.82, the assumed prior implies a confidence interval of 0.0 to 0.4. Graph 4 shows the distributions of the OLS estimator, the prior and the mixed estimator. Since the OLS distribution is very flat - reflecting the fact that the data are silent on the true value of the parameter - the procedure attaches considerable weight to the prior information.

Table 1
OLS estimates of parameters

Output equation							
a_1	0.42	a_2	– 0.31			R-sq	0.50
se	(0.20)	se	(0.11)				
Inflation equation							
b_1	0.30	b_2	0.16	b_3	– 0.08	R-sq	0.85
se	(0.26)	se	(0.24)	se	(0.02)		

So far we have demonstrated how the use of the prior information affects the parameter estimates of a_2 and b_1. Next we show how this information changes our view of the transmission mechanism by calculating impulse responses analogous to those reported in Graphs 1 and 2. Consider first the responses of the output gap to a tightening of monetary policy. Comparing Graph 5 with Graph 1, we see that the use of prior information has little impact on the results, although the confidence bands are somewhat tighter. This is not surprising, since the OLS estimate of the impact of real interest rates on output was relatively precise, and we assumed that the prior mean on this parameter was similar to the OLS estimate.

Turning to the impact of monetary policy on inflation, however, Graph 6 shows that using the prior information has a clear impact on the result. While the point estimates are roughly similar to those

[4] For simplicity, each coefficient is estimated individually.

[5] Thus, we assume that a 95% confidence interval spans the range -0.5 to -0.1.

resulting from solely using the information in the data, the estimated confidence band is much narrower. Indeed, the decline in inflation in response to a tightening of monetary policy is significantly different from zero.

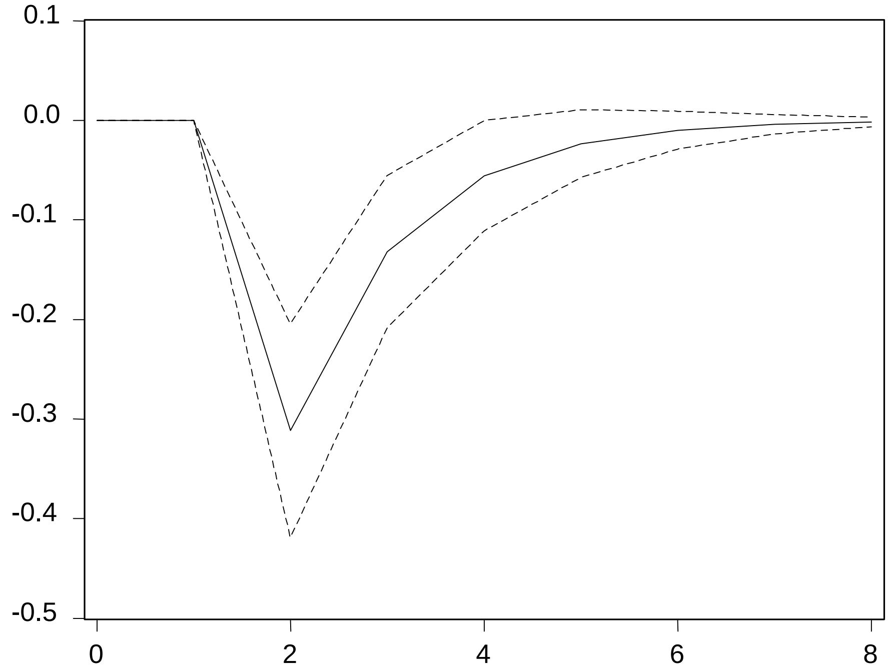
6. Conclusion

This note has illustrated how prior information can be used to study the transmission mechanism of monetary policy in situations in which the data itself are not very informative. While the approach is promising, it should be emphasised that the choice of priors can be a difficult task. Ongoing work at the BIS is focusing on how to specify prior distributions in a systematic and defensible manner.

Graph 1

Responses of output gap

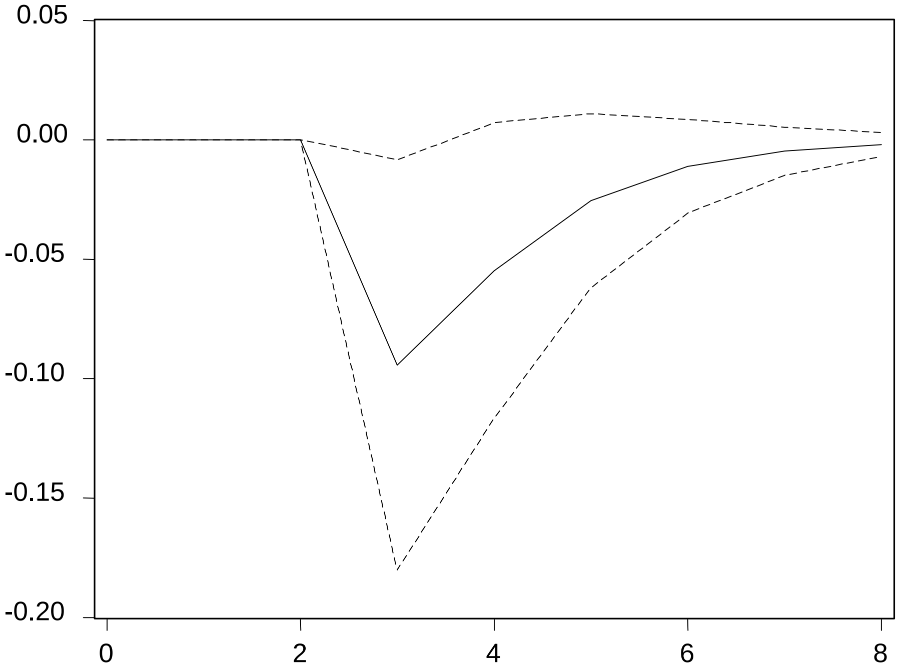
(OLS estimates)



Graph 2

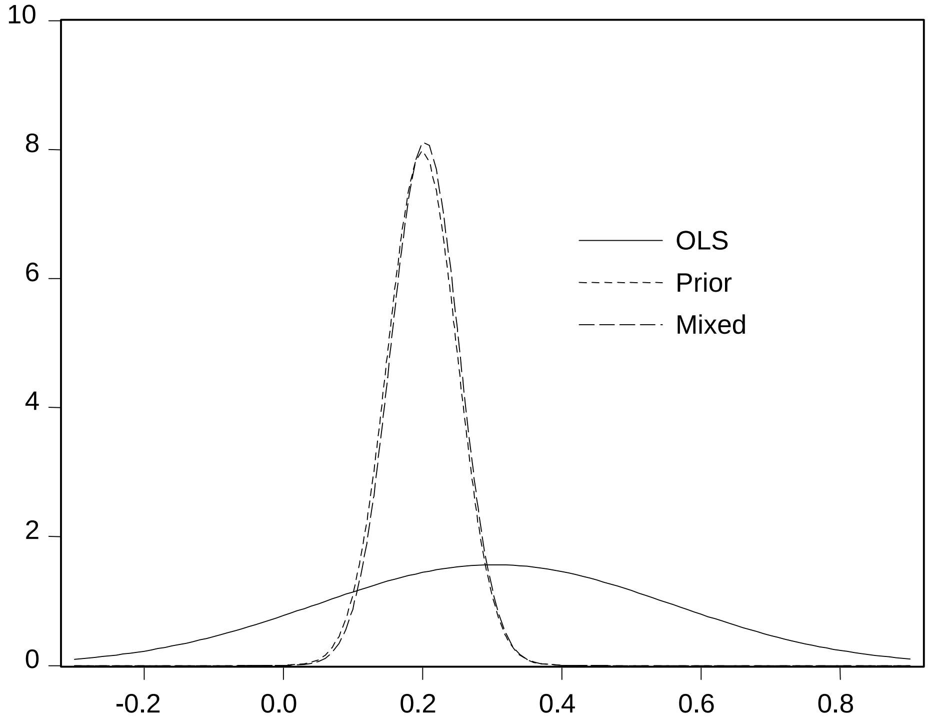
Responses of inflation

(OLS estimates)



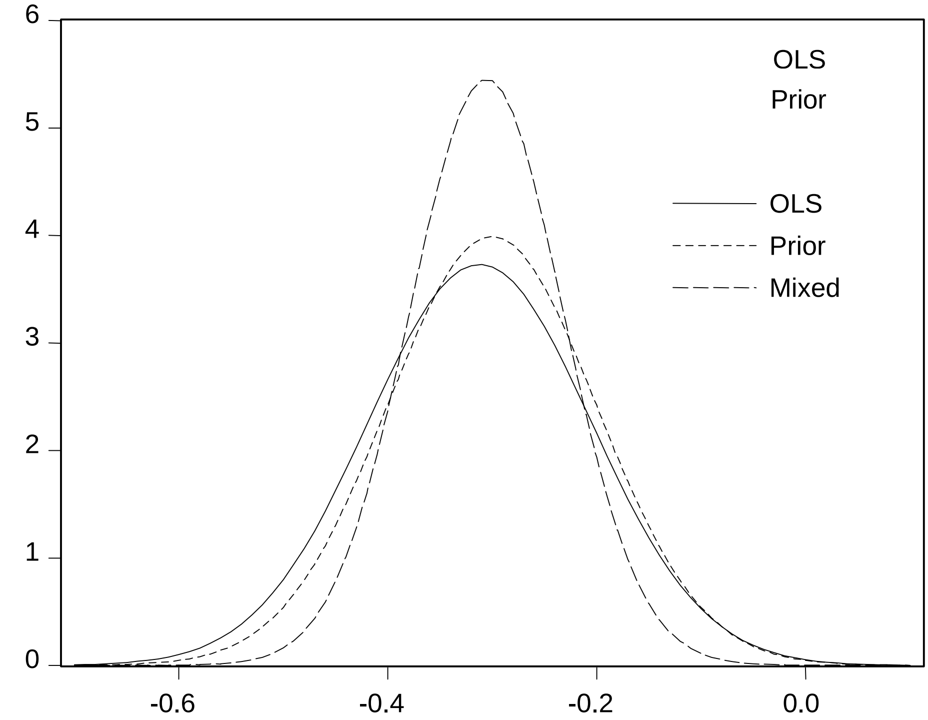
Graph 3

Impact of real interest rate on output



Graph 4:

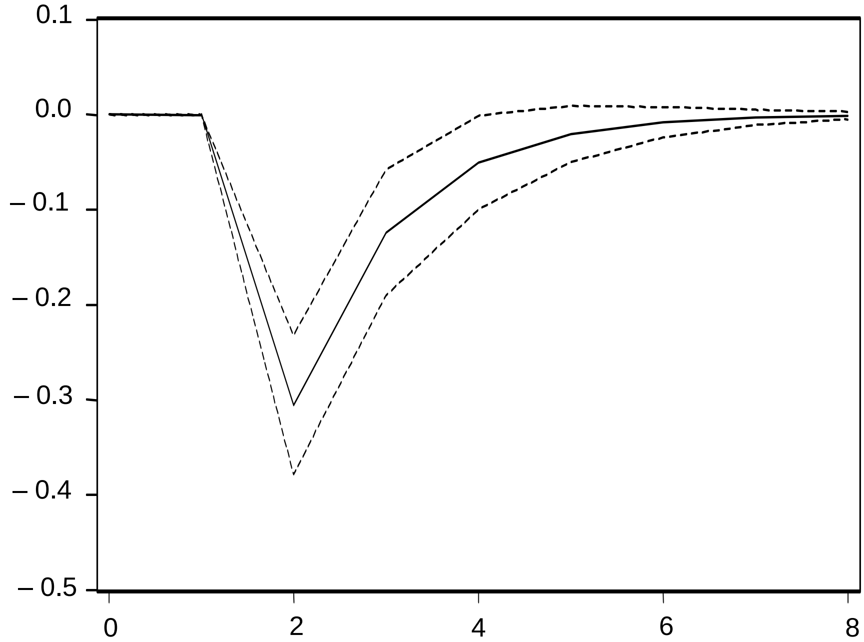
Impact of real interest rate on inflation



Graph 5

Responses of output gap

(Mixed estimates)



Graph 6

Responses of inflation

(Mixed estimates)